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It could rain: weather forecasting as a reasoning process

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Abstract

Meteorological forecasting is the process of providing reliable prediction about the future weathear within a given interval of time. Forecasters adopt a model of reasoning that can be mapped onto an integrated conceptual framework. A forecaster essentially precesses data in advance by using some models of machine learning to extract macroscopic tendencies such as air movements, pressure, temperature, and humidity differentials measured in ways that depend upon the model, but fundamentally, as gradients. Limit values are employed to transform these tendencies in fuzzy values, and then compared to each other in order to extract indicators, and then evaluate these indicators by means of priorities based upon distance in fuzzy values. We formalise the method proposed above in a workflow of evaluation steps, and propose an architecture that implements the reasoning techniques.

1. Introduction

The process of producing weather forecast is rather complex and should be represented as a linear workflow in which several steps are taken. The initial step consists in gather data from scratch, and can be derived by many eterogeneous sources. Data gathered by sensor networks and other sources are used in a few ways:

1. To provide the basic data to run the weather forecast models (initialization);
2. To help the forecaster to evaluate the results of a weather forecast model run (execution);
3. To habilitate the forecaster to build a conceptual scenario of the actual weather (remodelling);
4. To estimate the quality of a NWP system (verification - outside the scope of the present work).

In general, data gathering produces scratch unfolded data, consisting in measures of the observational variables in points on the land or in the atmosphere. These cab either be real measures taken from sensors, or the results of a run of x a weather forecast model is the second step of the process identified above. Essentially, the output of a model consists of a set of four-dimensional matrices, each entry of these matrices being a scalar or vectorial measure,

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valued in a geographic referential point and in a given instant of time. The measures used in all the models currently considered in literature are:

- Humidity (scalar);
- Air pressure (scalar);
- Temperature (scalar);
- Wind speed (vectorial).

Models in specific applications such as agrimeteorology may also include indices of pollution, including particulate matter or pollen. The forecast models are formed by two classes of matrices: analysis (1) and previsional (2). Models are classified also in two types, global (a) and local (b). The analysis matrices derive from three sources:

- Meteorological stations at land;
- Wheather balloons;
- Satellites.

The analysis matrices of local and global models assign one value of the associated variable to an instant of time and a point in a 3D space, that represents either a direct measure of the value of the variable obtained by some of the three main sources above mentioned, in that point, or an indirect measure obtained by employing an expansion model for other measures taken by any information source in the near vicinity of the measured point.

Previsional matrices instead contain values of the forecast of the measures in the same points of the analysis matrices and in instants of time in a future point with respect to the moment in which the measures are used to initialize the forecast process. These previsional matrices are sparser in terms of time instants then the analysis ones (namely the sample instants of the previsional matrices are less than the sample instants of the analysis oense), and also posponed in the future to an instant of time that occurs later with respect to the last instant of the analysis, for the process of computing these forecast is anything but instantaneous.

The single production of a model, including the creation of the analysis and the forecasts, is called a *run*; modern NWP Models are produced four time a day, at hours 00, 06, 12 and 18, because these are the date in which the most important data are available. Expecially 00 and 12 are at the present time the more complete run for global NWP model. The models generate the forecasts by solving systems formed by a huge number of partial derivates differential equations, that are solved numerically, typically by employing finite elements algorithms. Reliability of these models are very variable in time and space, , as it can differ beetween single runs of the same model.

The third step of a model is the one that involves simultaneously *decision theory* and *reasoning* approaches. It consists in evalutating the models in two ways:

- Directly, to establish metaproperties of the models, in particular *reliability*;
- Comparatively, to establish the priority among models in the decision process.

Final step consists in the generation of the *meteorological bulletin*. The full workflow of the weather forecast process is described in details in Section 4. In this paper we generalize an approach that implements the above mentioned workflow as applied in a given case study, the Agenzia Regionale per la Protezione dellámbiente del Veneto, henceforth ARPAV, within the weather forecast team.

The rest of the paper is organized as follows. Section 2 summarizes related work in the field. In Section 3 we introduce the context in which the experimental framework has been settled, and in Section 5 describes a formal model of the steps introduced above, in particular evaluation and comparison of models and scratch data. Section 6 is devoted to provide some examples of the result of applying the system defined in Section 5 taken from the context aforementioned, and finally Section 7 takes some conclusions and sketsches future work.

2. Related work

The usage of intelligent decision technologies in the weather forecast process is a long-term research effort. Since the pioneering studies [6, 11, 26], and further engineering investigations on the commercial solutions [27] a first attempt going in the same direction devised in this paper appeared in the Nineties [15] and has inspired many studies thenceforth, in many different specialised fields including snow research, marine forecasting and agrimeteorology [21, 23, 19, 14, 5, 22, 12, 13]. The ontological appraoch has been applied to forecasting quite recently [1]. Usage of the internet of things [20] has also recently taken light in the field of meteorological forecasting.

The reasoning system proposed in this paper is a work in progress. As explained in Section 7, we have to further develop it in several directions. Thus, at the moment, a direct and full comparison with the state of art is quite hard. Notwithstanding, if previously cited papers represent the main references for the role of formal reasoning in forecasting, we can briefly retrace the main technical inspirations of the framework we propose here. For the purpose of this research the main topics to refer to are sensor-based applications, and non-monotonic reasoning. A specific effort on the usage of non-monotonic deduction systems in sensor-based applications (clearly related to the initial part of the forecasting process) has been carried out by some of the authors in the recent past [31]. In particular, the defeasible flavour of the system is inspired to the framework developed in [10] and the architectural model we proposed is based on the one (already implemented and working) described in [30]. This effort base itself on several basic studies regarding the revision processes and its interference with non-monotonic reasoning, in particular in the field of business process compliance [18, 28, 16, 17].

3. Context

The ARPAV agency is a complex organization, that has many further duties in addition to the one of meteorological forecasting, with particular concern in the fields of pollution control and monitoring, terrestrial and water surveying for meteorological emergencies, and many other ones.

Very generally we can disciminate three types of models: (a) global, also known as *at synoptic scale* (close to 1000 miles scale), (b) intermediate, also known as *at mesoscale* (close to 100 miles), and (c) local, also known as *at limited area* (close to 10 miles).

The most common models used in meteorological forecasting are listed below.

- GFS, american model (synoptic scale);
- ECMWF, european model (synoptic scale);
- NOGAPS, U.S. Navy model (synoptic scale);
- UKMO, UK model (synoptic scale);
- GEM, canadian model (synoptic scale);
- WMC, russian model (synoptic scale);
- JMA, japanese model (synoptic scale);
- BOM ACCESS, australian model (synoptic scale);
- RAMS, mesoscale model;
- BOLAM, limited area model (LAM);
- DALAM, limited area model (LAM);
- MM5, limited area model (LAM).

For the forecasting of the northern east of Italy, where Veneto is geographically situated, the meterological team uses output of main european global model, the model developed at ECMWF, as encouraged by the National Civil Protection System; secondly it is employed the american GFS model, mainly for a comparison with the results given by the ECMWF model. Moreover the global model Arpge, developed by MeteoFrance, it is available specifically for the Mountain meteorology team in Arabba. At the mesoscale the forecasting team at the Military Aeronautics essentially employ COSMO-ME, while the Civil Protection related Agencies, as ARPAV, employ the version COSMO5M (previously called LAMI model).

4. System architecture

The system aim is to produce a better weather forecast, given meteorological models and having data gathered from the field, as summarized in Figure 1.

We briefly describe some phases, corresponding (from left to right) to the blocks in the process flow.

phase 1 A model runs and is delivered to the forecaster. models are coherent to the physics of the atmosphere.

phase 2 Evaluation of the single local forecasting as compared to the real data obtained by sensors

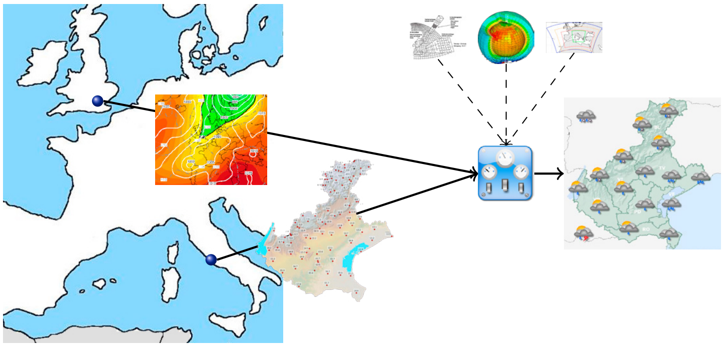

Fig. 1. The operative concept of the system

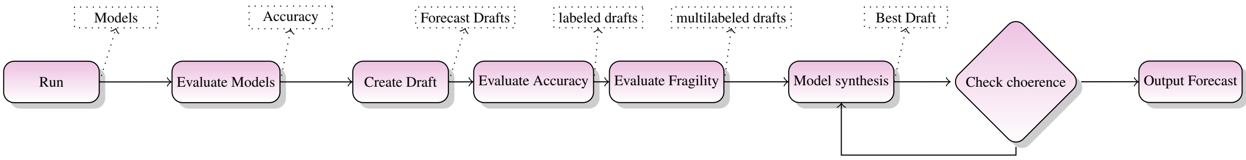

Fig. 2. Process flow

phase 3a Polling models and real values on a qualitative area

phase 3b Evaluation of accuracy for individual forecasting; tagging of each element of subphase 3a for each model

phase 3c Evaluation of fragility of models of individual forecasting;

phase 4 Model Synthesis: every individual judgement generated in phase 3 is compared against analogous judgments in different models, and best individual judgments are chosen

phase 5 Models are evaluated against coherence. Incoherent models are rejected and phase 4 is repeated without these models

phase 6 Delivery of judgments

The system is made of several modules, each one with a single responsibility; the logic model of which is reported in Figure 3.

Here the description of each module:

Data Gather: this component aims at the retrieval of raw informations form a specific source (i.e. Temperature, Humidity) connecting to a sensor network and or a data source. To add a new source to the system (eg. Sea Status) the only implementation to be done are the one to this module.

Model Generator: this module takes as input cleaned data and their evaluated confidence and gives as output a set of populated models suitable to be later exposed to the *Model Evaluator*

Model Evaluator: this module takes as input populated models and computes data such as *accuracy* and *fragility* so that the *Forecast Generator* can operate

Forecast Generator: this module takes as input populated models and their *accuracy* and *fragility* data and gives *forecast drafts* to be examined by the *Forecast Evaluator*

Forecast Evaluator: this module takes as input forecast drafts and makes evaluations on several parameter so that its output are a set of metadata, or *labels*

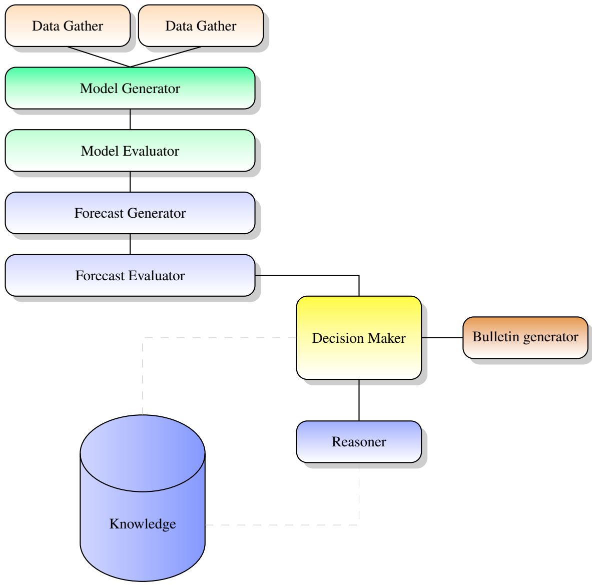

Fig. 3. Logic model of system architecture

Decision Maker: this is the actual core of the system, the one which aim is to decide which model will give best performances

Reasoner: this module is the "brain" of the system: it actually applies logic deduction system to make decisions about which forecast draft is to be defined the "best one"

Knowledge base: where the knowledge base is stored; the *Reasoner* will access it for reasoning and the *Decision Maker* will increment it after evaluation of the results of the reasoner

Bulletin generator: tho module provides visualization of all data, building the output of the system as a "pdf" file or hypertexts

5. A defeasible fuzzy system for meteorological forecasting

The reasoning process of the forecaster is described in the schema below, that is formed by technical steps implementing the workflow described in Section 4.

As a first, preliminary step in the formalization of reasoning meteorological forecasting is based on, we introduce a logical framework, called MeteoLOG. MeteoLOG is majorly inspired to three logical traditions: defeasible logic [17], labeled deduction systems [24, 25, 32, 33, 9] and fuzzy/non-deterministic/probabilistic frameworks [12, 2].

The main idea is to represent the heuristic knowledge described by the the previously defined architecture, that couples deductive, empirical and fuzzy reasoning.

The alphabet of MeteoLOG is based upon some classes of variables: *environmental variables*, denoted as x, y, z (possibly indexed), representing dimensions of three dimensional geografical coordinates; *time instants variables*, denoted by τ, possibly indexed.

On these variables we do not introduce quantifiers.

We build three types of propositional (ground) assertions and four types of modal assertions.

Rough data assertions (RDA) RDA consist in four-dimensional predications on a space point $\langle x, y, z, \tau\rangle$ of *temperature* (T), *humidity* (H), *air pressure* (P), and three predication modeling (vectorial components of) *wind speed* of the kind (V_x, V_y, V_z) such as:

$$\begin{array}{lll} T(x,y,z,\tau,t) & H(x,y,z,\tau,h) & P(x,y,z,\tau,p) \\ V_x(x,y,z,\tau,v_x) & V_y(x,y,z,\tau,v_y) & V_z(x,y,z,\tau,v_z) \end{array}$$

For instance, the assertion Temperature on ground level, point of measure (45.4392242,11.00145180000004) on GPS coordinates, on 06/04/2018 14:05:00 was 17C degrees is represented by T(45.4392242,11.00145180000004,0,06/04/2018::14:05:00CET,17C).

Weather conditions assertions (WCA) . WCA regard the qualitative variables of *sky*, *precipitation/showers*, *wind*, *sea*, *temperature*, *air visibility*, *humidity*, on the following scales:

❍ **Snowfalls**:
- Blizzard (Bϕ)
- Snowstorm (Sϕ)
- Snow flurry (SFϕ)
- Snow squall (SQϕ)
- Snowburst Sb(ϕ)
- Blowing snow (BSϕ)
- Drifting snow (DSϕ)

❍ **Wind**:
- Light Winds (LWζ)
- Moderate Winds (MWζ)
- Moderate Winds (MWζ)
- Fresh Winds (FWζ)
- Near Gale (NGζ)
- Gale (Gζ)
- Strong Gale (SGζ)
- Storm (Sζ)
- Violent Storm (VSζ)

❍ **Sea**:
- Calm (Cμ)
- Slight (Sμ)
- Moderate (Mμ)
- Rough (Rμ)
- Very Rough (VRμ)
- High (Hμ)
- Very High (VHμ)
- Phenomenal (Pμ)

❍ **Sky conditions**:
- Clear or Sunny Skies (CSσ)
- Partly Cloudy (PCσ)
- Mostly Cloudy (MCσ)
- Cloudy (Cσ)
- Overcast (Oσ)

❍ **Precipitation**:
- No precipitation (NOπ)
- Very Light Rains (VLπ)
- Light Rains (Lπ)
- Moderate Rains (Mπ)
- Heavy Rains (Hπ)

❍ **Rainshowers**:
- Scattered (Sρ)
- Isolated (Iρ)
- Occasional (Oρ)
- Squally (Sqρ)
-

❍ **Visibility**:
- Clean (Cν)
- Misty (Mν)
- Foggy (Fν)
- Hazy (Hν)

Weather conditions assertions are the output interpretations of the forecasting prevision, that, as explained below, can be validated or refused up to a belief revision depending on stability conditions of the forecasting scenario, validation on the ground values obtained by direct measures and conditions of coherence of the obtaiend combo model.

Scale condition assertions (SCA) SCA provide an interpretation scale for a given meteorological condition on an instant of time of the form $\Theta(\tau, cond)$, where cond is scaled by Simple ($\sigma\chi$), Regular ($\rho\chi$), Delicate ($\delta\chi$), Very delicate ($\Delta\chi$).

SCA have a direct effect on the evaluation of weather condition assertions.

Model-derived assertions (MDA) MDA are obtained by labeling Rough Data Assertions.

Labels represent *contextualized methods*, i.e., a forecasting method applied to a data gathering sample, performed in a given instants of time, weighted with an accuracy probability.

Formally, labels are tuples of the kind $\langle \lambda, a, \epsilon, \tau \rangle$, where:

- λ, possibly indexed, represents a model (within which the assertion is obtained);
- a, possibly indexed, represents the accuracy of the model (a percentage);
- ϵ, possibly indexed, represents data reliability, i.e. the accuracy (a percentage) of input data w.r.t. real world values;
- τ, possibly indexed, represent time instants in which the assertion is derived by the model λ (the execution time).

We denote labels with $l, r, s...$ (possibly index), and we call **Lab** the set of labels.

$$
\begin{array}{lll}
l : T(x, y, z, \tau, t) & l : H(x, y, z, \tau, h) & l : P(x, y, z, \tau, p) \\
l : V_x(x, y, z, \tau, v_x) & l : V_y(x, y, z, \tau, v_y) & l : V_z(x, y, z, \tau, v_z)
\end{array}
$$

In the following, we sometimes denote assertions (both rough and model-derived), with $\phi(\tau)$, possible indexed, highlighting the time variable.

Model comparison assertions . We import now a defeasible flavor, by stanting a priority relation between labeled assertion: $\langle \lambda_1, a_1, \epsilon_1, \tau_1 \rangle : \phi_1(\tau) \succ \langle \lambda_2, a_2, \epsilon_2, \tau_2 \rangle : \phi_2(\tau)$ holds in one of the following cases:

1. $(\tau - \tau_1) > (\tau - \tau_2)$
2. $a_1 \geq a_2 \wedge (\tau - \tau_1) > (\tau - \tau_2)$
3. $a_1 < a_2 \wedge (\tau - \tau_1) > (\tau - \tau_2) \wedge \epsilon_1 > \epsilon_2$

Notice that temporal information plays a major role. In particular, the time interval involved in the forecasting is limited by two time instants: the one in which we apply a method (the τ component in the label) and the one in the assertion. For the sake of simplicity, without any loss of generality, we highlight in the assertion the time limit for which the forecasting is supposed to hold.
Looking for priority cases above, the most recent model-based assertion always prevails. Moreover, more accurate model-based assertion prevails, but only up to a better data input accuracy.

We presented minimal equipment to logically formalize the assertion-based part of the formal reasoning at the base of meteorological forecasting.

We show that we need a complex workflow to describe it, since we have several aspects to consider. On the logical side, this will drive the definition of a set of proof conditions on the one hand, and of a semantics for the fuzzy logical layer on the other one.

We recall here main steps of the reasoning system, pointing out crucial facts.

1. RA represents ground logical knowledge, obtained by data collection.
2. Once forecasting methods are applied, the collected set of MDA represent our assertional box.
3. Forecasting are represented by WCA, obtained by MDA by label elimination.
4. WCA can need belief revision:

   - When the forecasting of a single model is provided, we might observe future and past of that particular model, and since we do have rough data collected in the ground, the validity of a model is naturally related to the errors made in forecasting when the model is applied in the past of a real data collection. In fact, if that forecasting contradicts explicitly some rough data, the model should not be valid. This applies to a single error, but very generally we should consider an amount of errors that gives out a percentage of validity. If the number of errors is over a given percentage (that depends on the evaluations of point 4) we have an invalidation.
   - When a model takes some forecasting conclusion, then that model validity is not independent of the condition of the weather. When the condition under analysis is *delicate* or *very delicate* the forecasting errors are more common, and less important, in the validity analysis. On the other hand, it is very compromising for a model to make forecasting errors when the condition is simple or regular. Rules to assert validity depend upon coherence of the thresholds.

The output of a model is **summarized** by the forecaster with a scheme that associates each subregion of the reference area onto the judgments introduced above. In Figure 5 the Region Veneto is split into small subregions. On the left part of the figure we list sample measures and summary judgment of an hypothetical model.

6. Forecasting examples

A referred to the method introduced in this paper, we illustrate the reasoning steps taken by a forecaster during the process of producing a bulletin for the afternoon of 7/04/2018.

Considered models:

- ECMWF (Global model);
- GFS (Global model);
- COSMO5M (LAM);
- LAMI7 (LAM).

For each model the forecaster consulted the runs of time 00 on 6/04/2018 and time 12 of 5/04/2018. The first part of the model analysis consists in summarising the forecasting of the models themeselves at synoptic scale.

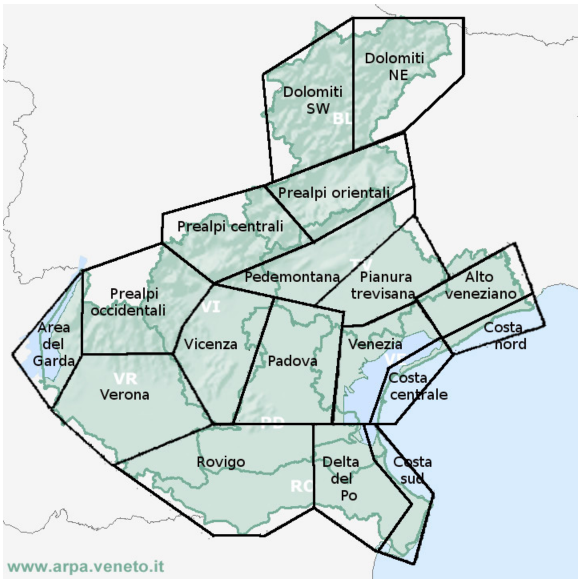

Fig. 4. The Veneto region partition.

- On the subregion marked as Dolomiti NE (Northeastern Dolomiti), several forecasting ground points provide forecastings for the values of temperature, air pressure, wind speed and humidity.
- Summary of the values are interpreted in the sense introduced by the judgments devised above.
- Judgments are expressed by the forecaster as derived from the above mentioned summary.
- *Air lift and temperature negative gradient lead to precipitation* is a typical rule of interpetation employed to transform a set of forecasting on single points in the maps.

Synoptic situation

Run00 of ECMWF shows a weak southern flow, along with a modest depression on the east, going northbound on Slovenia and Austria. The effects of such a depression, that does not result deep, but can marginally influence an anticyclonic context, typical of the spring period, and relatively stable, are difficult to forecast in general. Specifically there are no well-determined *forcing movements*.

At first it rises the hypothesis that some local precipitation on the east mountain area (Dolomiti Bellunesi). This should be checked by comparing conclusions on precipitation of the models with real data gathered on the ground.

Situation stability

The last four runs of the reference model, the situation has been quite stable, with some uncertainty on the position of the centre of low pressure.

Model-based inference on precipitation

Forecasted precipitaiton between 12 and midnight of Saturday 7/04/2018 on Dolomiti Venete varies between 0 (ECMWF 00 and ECMWF 12) and 1-3 millimiters in some local points (GFS, COSMO5M and LAMI7). Errors in local precipitation forecasting can be divergent, especially in presence of convections. In other situations numeric modelling provides an estimate of a reduced precipitation, whilst locally we could find consistent rainshowers. We therefore need to deepen the analysis in a different direction, without limiting to the numeric forecasting only.

The conceptual bases and specific test planning

The situation stresses the fact that precipitation should be framed within a weak convection context, both from a temperature and from a dynamic nature (presumably intereferring). We need to understand the daytime heating and the dynamics of the passage of the weak depression.

Specific situation analysis

The analysis of the vertical speed on the reference model highlights a rather weak convection activity on the lower layers of the atmsphere in the afternoon of Saturday with a slight uplift (800 hPa) contrasted by a weak subsidence in the upper layers (700 hPa and higher). A possible explanation of the contradictions emerged so far is that the local-scale model might introduce some *finer* data that indeed contrasts the subsidence on upper levels, leading to a modest effect of the forecasted vertical convection. The observation of instability indices of the reference model suggests to exclude convection effects.

Conclusions of the forecasting
The forecaster shall evaluate the option of inserting in the bulletin some fuzzy expression able to communicate the low probability of precipitation on the Dolomiti Venete. A possible formula could be: possible afternoon Scattered Rainshowers in the east Mountain of Veneto. General evaluation is that weather should be forecasted as *good* in a context of spring variability, anyhow with a satisfying recent forecasting results. Numeric modelling are unable to establish to forecast precisely convections (including those actually not producing rainshowers at all). Generally the forecaster knows that the local models tend to overestimate this phenomenology for structural reasons and GFS model results, in turn, rather tough in terms of grid, often being unprecise, especially in presence of complex orographic context. Also forecasting of precipitation remain on quantities and aereals rather limited (1-3 mm and 2-4 grid points on models with 5km resolution). Lastly, environmental conditions and impact of the user are not critical, due to the area and the season, being thus the users quite well prepared to tolerate imprecisons. Scattered rainshowers, particularly if not intense and short in time would not arise specific criticisms on the forecaster accuracy. All these summarized, the forecaster will not insert rainshowers in the bulletin, finally producing the following:

> *Daytime climate will be mild at all altitudes. In late afternoon some low-layered clouds are extending over the whole Veneto mountain. No precipitation.*

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7. Conclusions

In this paper we envisioned an architecture to provide assistance for meteorolists in the process of producing weather forecast. The basic scheme is a reasoning technology able to simulate the decision process made by the forecasters in producing weather bulletins.

The development effort is still on, and we are going into the development of a technology prototype that incorporates the notions analysed in this paper. The research team includes a forecaster of the ARPAV weather forecasting service, one of the most valuable forecasting service in Italy.

There are various ways of extending this study. A part from the developmental one and the subsequent experimental work, the very same architecture could be significantly extended. One basic issue regards the portability of the approach, that has been intentionally devised for situations quite different from the Veneto area, where the project we are working at is in place. One basic problem with the solution we discussed it regards the scales. These are generally applicable, but there are many environmental conditions in which it would be worth either to extend them by including further scales (as in for instance the northern countries such as Canada, Alaska or Norway, Russia and so for) for which *ice conditions* could be needed as a specific scale, or to modify the values in the scale or the thresholds (for instance this can concern Philippines, where wind values vary signficantly with respect to the introduced general scale, or the USA, where the thresholds for rainshowers are different in the north and in the south of the country).

To deal with these sorts of problems it is worth introducing notions related to *meaning negotiation* in particular those treated in studies concerning social networks [4].

Measures of risk, and logical approach to these is also crucial in the further development [8]. Moreover a systematic usage of geographic rich information is needed and the logical layer shall be extended further with these aspects as suggested in [7]. Finally, we plain to fully develop the logical framework MeteoLOG, by defining a suitable semantics and a natural deduction inference system[29, 3].

References

[1] A. Agresta, G. Fattoruso, M. Pollino, F. Pasanisi, C. Tebano, S. De Vito, and G. Di Francia. An ontology framework for flooding forecasting. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 8582 LNCS(PART 4):417–428, 2014.

[2] F. Aschieri and M. Zorzi. Non-determinism, non-termination and the strong normalization of system t. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 7941 LNCS:31–47, 2013.

[3] F. Aschieri and M. Zorzi. On natural deduction in classical first-order logic: Curry-howard correspondence, strong normalization and herbrand's theorem. *Theoretical Computer Science*, 625:125–146, 2016.

[4] E. Burato, M. Cristani, and L. Vigan. A deduction system for meaning negotiation. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 6619 LNAI:78–95, 2011.

[5] L.E. Carr III, R.L. Elsberry, and J.E. Peak. Beta test of the systematic approach expert system prototype as a tropical cyclone track forecasting aid. *Weather and Forecasting*, 16(3):355–368, 2001.

[6] B.J. Conway. Expert systems and weather forecasting. *Meteorological Magazine*, 118(1399):23–30, 1989.

[7] M. Cristani and N. Gabrielli. Practical issues of description logics for spatial reasoning. volume SS-09-02, pages 5–10, 2009.

[8] M. Cristani, E. Karafili, and L. Viganò. Towards a logical framework for reasoning about risk. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 7465 LNCS:609–623, 2012.

[9] M. Cristani, F. Olivieri, C. Tomazzoli, and M. Zorzi. Towards a logical framework for diagnostic reasoning. In *Agents and Multi-Agent Systems: Technologies and Applications 2018. Proc. of KES-AMSTA-18, https://doi.org/10.1007/978-3-319-92031-3_14*, pages 1–12. Springer, 2018.

[10] M. Cristani, C. Tomazzoli, E. Karafili, and F. Olivieri. Defeasible reasoning about electric consumptions. In *30th IEEE International Conference on Advanced Information Networking and Applications, AINA 2016, Crans-Montana, Switzerland, 23-25 March, 2016*, pages 885–892, 2016.

[11] Michel C. Desmarais, Frances de Verteuil, Peter Zwack, and Denis Jacob. Stratus: A prototype expert advisory system for terminal weather forecasting. pages 150–154, 1990.

[12] D. DomaÅska and M. Wojtylak. Application of fuzzy time series models for forecasting pollution concentrations. *Expert Systems with Applications*, 39(9):7673–7679, 2012.

[13] D. DomaÅska and M. Wojtylak. Explorative forecasting of air pollution. *Atmospheric Environment*, 92:19–30, 2014.

[14] P.M.B. Fhn. An overview of avalanche forecasting models and methods. *Publikasjon - Norges Geotekniske Institutt*, (203):19–27, 1998.

[15] Eli Goldberg. Fog. synthesizing forecast text directly from weather maps. pages 156–162, 1993.

[16] G. Governatori, F. Olivieri, E. Calardo, A. Rotolo, and M. Cristani. Sequence semantics for normative agents. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 9862 LNCS:230–246, 2016.

[17] G. Governatori, F. Olivieri, S. Scannapieco, and M. Cristani. The hardness of revising defeasible preferences. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 8620 LNCS:168–177, 2014.

[18] G. Governatori, F. Olivieri, S. Scannapieco, A. Rotolo, and M. Cristani. The rationale behind the concept of goal. *Theory and Practice of Logic Programming*, 16(3):296–324, 2016.

[19] B. Hansen. Sigmar: a fuzzy expert system for critiquing marine forecasts. *AI Applications*, 11(1):59–68, 1997.

[20] A. Kulkarni and D. Mukhopadhyay. Internet of things based weather forecast monitoring system. *Indonesian Journal of Electrical Engineering and Computer Science*, 9(3):555–557, 2018.

[21] V.R. Kumar, C.Y.C. Chung, and C.A. Lindley. Toward building an expert system for weather forecasting operations. *Expert Systems With Applications*, 7(2):373–381, 1994.

[22] C. Mahabir, F.E. Hicks, and A.R. Fayek. Application of fuzzy logic to forecast seasonal runoff. *Hydrological Processes*, 17(18):3749–3762, 2003.

[23] Rose M. Marra, David H. Jonassen, and Paul Knight. Use of expert system generation to promote knowledge synthesis in a meteorology forecasting course. pages 475–479, 1996.

[24] Andrea Masini, Luca Viganò, and Margherita Zorzi. A Qualitative Modal Representation of Quantum Register Transformations. In G. Dueck, editor, *Proceedings of the 38th IEEE International Symposium on Multiple-Valued Logic (ISMVL 2008)*, pages 131–137. IEEE Computer Society Press, 2008.

[25] Andrea Masini, Luca Viganò, and Margherita Zorzi. Modal deduction systems for quantum state transformations. *J. Mult.-Valued Logic Soft Comput.*, 17(5-6):475–519, 2011.

[26] John McCarthy and Robert J. Serafin. Advanced aviation weather system based on new weather sensing technologies. pages 228–239, 1990.

[27] W.R. Moninger. Shootout-89, an evaluation of knowledge-based weather forecasting systems. *Machine Intelligence and Pattern Recognition*, 10(C):457–458, 1990.

[28] F. Olivieri, G. Governatori, S. Scannapieco, and M. Cristani. Compliant business process design by declarative specifications. *Lecture Notes in Computer Science*, 8291 LNAI:213–228, 2013.

[29] Dag Prawitz. Ideas and results in proof theory. In J.E. Fenstad, editor, *Proceedings of the Second Scandinavian Logic Symposium*, volume 63 of *Studies in Logic and the Foundations of Mathematics*, pages 235 – 307. Elsevier, 1971.

[30] Simone Scannapieco and Claudio Tomazzoli. Ubiquitous and pervasive computing for real-time energy management and saving - A system architecture. In *Proceedings of the 11th International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing (IMIS-2017), Torino, Italy, 10-12 July 2017.*, pages 3–15, 2017.

[31] C. Tomazzoli, M. Cristani, E. Karafili, and F. Olivieri. Non-monotonic reasoning rules for energy efficiency. *Journal of Ambient Intelligence and Smart Environments*, 9(3):345–360, 2017.

[32] Luca Viganò, Marco Volpe, and Margherita Zorzi. Quantum state transformations and branching distributed temporal logic - (invited paper). In *Logic, Language, Information, and Computation - 21st International Workshop, WoLLIC 2014, Valparaíso, Chile, September 1-4, 2014. Proceedings*, pages 1–19, 2014.

[33] Luca Viganò, Marco Volpe, and Margherita Zorzi. A branching distributed temporal logic for reasoning about entanglement-free quantum state transformations. *Inf. Comput.*, 255:311–333, 2017.